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13. ABSTRACT (Maximum 200 words)

This research report presents a procedure for landmine classification using an artificial neural network that can respond to complex-valued input data. This is because the acquired data in the form of scattering parameters at different frequencies are complex-valued and disregard of the phase works against the proven importance of phase in multidimensional signal processing. The complex-valued backpropagation algorithm, and its variants are implemented on acquired data to classify mines of different types and shapes. The importance of noise-contaminated phase as well as the role of partial phase information in image reconstruction is also investigated. The role of wavelet superresolution for multiresolution analysis of landmines in particular and image analysis in general is also reported. Analysis of an image acquisition system composed of an array of sensors, where each sensor has a subarray of sensing elements of suitable size, is provided for increasing the spatial resolution and implement filtering of image sequences beyond the performance bound of technologies that constrain the manufacture of imaging devices. Military and commercial applications of the research are highlighted by videomosaicing and superresolution of regions of interest from a real noisy and blurred video sequence.

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IMPROVED LANDMINE DETECTION BY COMPLEX-VALUED ARTIFICIAL NEURAL NETWORKS

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REPORT FOR RESEARCH during the period

October 1, 2000 to September 30, 2002 that includes an approved no-cost extension from October 1, 2001 to September 30, 2002

Contents

Foreword

The detection and classification of antipersonnel land mine has become a topic of very high priority in recent years. Newer methods employ artifical neural networks for more accurate detection. This research report presents a procedure for landmine detection using a complex-valued neural network. This is because the acquired data in the form of scattering parameters at different frequencies are complex-valued and disregard of the phase works against the proven importance of phase in multidimensional signals. The complex-valued backpropagation algorithm, clearly and compactly derived, and its variants are implemented on acquired data to classify mines of different types and shapes. The importance of noise-contaminated phase as well as the role of partial phase information in image reconstruction is also investigated. Scopes for further research in this promising area and the use of unsupervised learning in artificial neural networks in conjunction with fuzzy logic for improved system performance over and above the good results already attained are substantiated.

The role of wavelet superresolution for multiresolution analysis of landmines in particular and image analysis in general is also reported. *Image sequence superresolution* (or, for brevity, superresolution) refers to methods that increase spatial resolution by fusing information from a sequence of nonidentical images, each uniformly sampled, and acquired in one or more of several possible ways. This set of nonidentical images, when superimposed, form a bigger image whose region of support is a nonuniformly sampled raster. Techniques to achieve high resolution (superresolution) essentially revolve around attempts to convert this nonuniformly sampled image to an uniformly sampled one. An image acquisition system composed of an array of sensors, where each sensor has a subarray of sensing elements of suitable size, has recently been popular for increasing the spatial resolution with high signal-to-noise ratio beyond the performance bound of technologies that constrain the manufacture of imaging devices. The technique for reconstructing a high-resolution image from data acquired by a prefabricated array of multisensors was advanced by Bose and Boo and this work was further developed by applying total least squares to account for error not only in observation but also due to error in estimation of parameters modeling the data.

1 Introduction

A comprehensive REPORT FOR RESEARCH conducted during the period October 1, 2000 to August 31, 2001 was submitted in September 2001 to the Army Research Office [1]. Another PROGRESS REPORT plus a few viewgraphs in MS Power Point with briefing comments and paper references was submitted to the Army Research Office on March 27 [2]. This report, therefore, is the FINAL RESEARCH REPORT for US ARMY GRANT DADD19-00-1-0539.

The ideal objectives of a land mine are two fold. First, the goal is to cause as much damage as is possible with the least amount of material, and second, the avoidance of detection is crucial so that the first goal can be successfully realized. The second objective has been of major concern in the task of detecting mines. One of the more promising avenues of research in this area involves the use of artificial neural networks [3]. More specifically artifical neural networks have, recently, been used to detect landmines from back-scattered radio frequency data [5]. The two-port complex-valued scattering parameters, which are the elements of a 2×2 scattering matrix that characterizes the two-port in terms of reflected and transmitted powers are measured at different selected frequencies [6]. The inputs to the network were the magnitudes of the four scattering parameters (s_{11}, s_{12}, s_{21}, and s_{22}) at the seven central frequencies (880-1120MHz) in 40-MHZ intervals. Thus, the phase information was not exploited. The phase contains the information relating to the occurrence of edges in an image. This leads one to believe that the use of phase information may help in the area of edge detection of the landmine so that a preprocessing step in [7]. of fourth-nearest-neighbor outlier removal of data points would not be necessary since these points would contain valuable information on the location of the boundaries of a mine. The importance of using the phase along with the magnitude is also natural because the measured data is complex-valued. Use of magnitude-only information, therefore, is incompatible with the nature of the acquired data, especially because valuable information is contained in the phase, which should not be summarily either discarded or de-emphasized.

During the past decade, the interest in seeking enhancement of spatial resolution lead-

ing to a high-resolution (HR) image from a sequence of degraded (undersampled, blurred, and noisy) low-resolution (LR) images has been notable. HR images are required in many areas including remote sensing, military surveillance and medical diagnosis. Landmine classification can also be facilitated by superresolution algorithms. It is usually not possible at the outset to achieve the desired resolution because of technology and cost constraints. For example, the technology of a charge-coupled device (CCD) is limited by factors like physical dimension, shot noise and parasitic effects. In applications like astronomical imaging, the reduced size and weight of a camera in a spacecraft or satellite affect its quality. The need to perform a trade-off between size, weight, and quality of the CCD array necessitates the design of superresolution algorithms to obtain the desired HR image.

This research focusses on two superresolution algorithms: one is wavelet-based and the other is Delaunay triangulation based. Preprocessing is performed prior to the implementation of the superresolution algorithm in order to prevent the singularity problem. Attention is directed to the selection of the mother wavelet and the mother scaling function. Then the postprocessing phase incorporating multiframe noise filtering and blur removal following the implementation of the superresolution algorithm is developed. The overall blind superresolution procedure is illustrated on synthetic sequences and also on video (degraded by unknown blur and noise) sequences supplied by the Air Force Research Laboratory.

2 List of Appendix

The following figures are listed in the Appendix.

1. Figure 1 supports the importance of phase in the presence of noise for image reconstruction. Figure 2 shows the overall artificial neural network model for object classification from partial phase information. It has been concluded that reconstruction from phase information is more error-resilient than reconstruction from magnitude information in the presence of additive signal-independent noise. When the phase information is blurred and noise is added, regularization algorithms improve the the estimate of a

reconstructed image from degraded phase. Details are available in the M. S. thesis of Hung-Sik Kim cited in the appropriate section below.

2. Figure 3 shows the the high resolution (HR) reconstuction task decomposed into two subtasks : interploation and restoration based on the image formation model adopted. This image formation model is used for atmospheric and motion blur (due to relative motion between object and image). The blurring process in this model occurs prior to geometric transformations that are used to characterize video camera motion like translation, zooming, panning, tilting, and rotation. The procedure for estimating the blurred HR image is called interpolation. The interpolated image could be noise filtered using a simple but effective multiframe noise filtering scheme proposed in this research. The case of unknown blur leads to the important practical case of robust blind superresolution, also initiated in this research. Superresolution methods based on first generation wavelets like B-splines and also the spatial tesselation scheme of Delaunay triangulation are developed and implemented.

3. Figure 4 show typical frames in a video sequence provided by the Air Force Research Laboratory (AFRL), Rome, New York. The blur and noise, that are sources of degradation, are unknown. Figure 5 is the videomosaic created from research under the sponsorship of an AFRL grant following camera motion parameter estimation using the projective model [8]. Two regions of interest (ROIs) are identified in Figure 5. Figures 6 and 7 compare the high resolution image of the ROIs with the low resolution counterparts based on blur identification, filtering and superresolution by the method of Delaunay triangulation developed in this research. Details are available in the Ph.D. dissertation of Surapong Lertrattanapanich cited in the appropriate section below and in the peer-reviewed journal paper [9] .

4. The spatial resolution of an image is often determined by imaging sensors. In a charge-coupled device (CCD) camera, the image resolution is determined by the size of its photo-detector. Although a CCD camera for HD (High Definition) images has already

been developed, it is still necessary to increase the resolution further for SHD (Super High Definition) images. Reducing the size of pixels (photo-detectors) is one way to increase resolution. However, the smaller the pixel size is, the smaller is the amount of light available for each pixel and the picture quality is degraded because the existence of shot-noise (causing variation of input) is unavoidable. Therefore, a new scheme is needed to synthesize high resolution images, beyond the physical device performance bound, by incorporating signal processing techniques. An alternative way is the use of prefabricated multiple identical image sensors shifted from each other by subpixel displacements as shown in Figure 10 and then reconstruct a high resolution image from multiple degraded low resolution images acquired from the multisensor array. The relationship between low resolution image sensor and hypothetical high resolution image sensor is shown in Figure 11 and an example is shown in Figure 12. Details are available in the Ph.D. dissertation of Jaehoon Koo cited in the appropriate section below and in the peer-reviewed journal papers [10], [10]. .

3 Statement of the Problem Studied

In the Fourier representation of signals, spectral magnitude and phase tend to play different roles and in some situations, many of the important features of a signal are preserved if only the phase is retained [4]. For examples, both phase-only and magnitude-only acoustic and optical holograms have been studied. For phase-only hologram [4](also referred to as kinoforms) only the phase of the scattered wavefront is recorded and the magnitude is assumed to be constant while in the magnitude-only hologram the phase is assumed to be zero and only the magnitude of the scattered wavefront is recorded.

Irregular (nonuniform) sampling theory and its numerical implementation, important in superresolution from a sequence of low resolution discrete signals, is well developed in the 1-D case due to the work of Kadec and others [12]. Results in the area of efficient robust reconstruction from irregular samples in the multidimensional case are of more recent vintage

and even the generalization of 1-D nonuniform sampling results to n-D is far from being straightforward. The first generation wavelet basis for reconstruction from nonuniformly sampled data was initially discussed in [13] and the importance of the selection of mother wavelet and scaling function (generated by discrete filter bank) has been demonstrated in [9].

In the high resolution reconstruction with multisensor array system, speed is important as well as the quality of the reconstructed image. The desired algorithm should be computationally efficient and process data as they are received. Another goal of this research is to investigate various aspects of high resolution image reconstruction like boundary error, regularization and subpixel displacement error estimation in the design and implementation of fast and robust algorithms. Interestingly, the multisensor array technology was designed by NASA to help reduce the costs and time associated with removing, calibrating, and reinstalling the many sensors on the Space Shuttle launch pads. It is now available for licensing. (see http://www.edi.gatech.edu/nasa/Multisensor

3.1 The importance of phase in signals and neural network implementation

In general, with reconstruction from magnitude-only holograms, the reconstructed object is not of much value in representing the original object whereas reconstructions from phase-only holograms have many important features in common with the original objects. Many of features of the original image are clearly identifiable in the phase-only image but not in the magnitude-only image. Several results for justifying the importance of phase will be shown with 1-D signal and multi-dimensional signal in this section.

3.2 Wavelet Superresolution

Superresolution produces high-resolution (HR) image from a set of low-resolution (LR) frames. The relative motions in successive frames are estimated and used for aligning the sample points in each frame into a HR grid. There are various types of models [8] used

to represent camera motion, namely, translation, rigid, affine, bilinear, and projective. The most general model is the projective model which has eight motion parameters. After registering all LR frames into a HR grid, the available samples distribute nonuniformly. Then the wavelet superresolution algorithm is applied in order to get the HR image.

During the past decade, the interest in seeking enhancement of spatial resolution leading to a high-resolution (HR) image from a sequence of degraded (undersampled, blurred, and noisy) low-resolution (LR) images has been notable. HR images are required in many areas including remote sensing, military surveillance and medical diagnosis. However, it is usually not possible at the outset to achieve the desired resolution because of technology and cost constraints. For example, the technology of a charge-coupled device (CCD) is limited by factors like physical dimension, shot noise and parasitic effects. In applications like astronomical imaging, the reduced size and weight of a camera in a spacecraft or satellite affect its quality. The need to perform a trade-off between size, weight, and quality of the CCD array necessitates the design of superresolution algorithms to obtain the desired HR image.

3.3 Multisensor Array Based Superresolution

An image acquisition system composed of an array of sensors, where each sensor has a subarray of sensing elements of suitable size, has recently been popular for increasing the spatial resolution with high signal-to-noise ratio beyond the performance bound of technologies that constrain the manufacture of imaging devices. Small perturbations around the ideal subpixel locations of the sensing elements (responsible for capturing the sequence of undersampled degraded frames), because of imperfections in fabrication, limit the performance of the signal-processing algorithms for processing and integrating the acquired images for the desired enhanced resolution and quality. With the objective of improving the performance of the signal-processing algorithms in the presence of the ubiquitous perturbation errors of displacements around the ideal subpixel locations (because of imperfections in fabrication) in addition to noisy observation, the errors-in-variables or the total least squares method is de-

ployed here. A regularized constrained total least squares (RCTLS) solution to the problem is given that requires the minimization of a nonconvex and nonlinear cost functional. Simulations indicate that the choice of the regularization parameter influences significantly the quality of the solution. The L-curve method is deployed to select the theoretically optimum value of the regularization parameter instead of the unsound but expedient trial-and-error approach. The expected superiority of this RCTLS approach over the conventional least squares theory based algorithm is substantiated by example.

4 Summary of the Most Important Results

This research focusses on two superresolution algorithms: one is wavelet-based and the other is Delaunay triangulation based. Preprocessing is performed prior to the implementation of the superresolution algorithm in order to prevent the singularity problem. Attention is directed to the selection of the mother wavelet and the mother scaling function. Then the postprocessing phase incorporating multiframe noise filtering and blur removal following the implementation of the superresolution algorithm is developed. The overall blind superresolution procedure is illustrated on synthetic sequences and also on video (degraded by unknown blur and noise) sequences supplied by the Air Force Research Laboratory. The connection between wavelet superresolution and DTHR algorithm is analyzed and a promising direction of future research on blind robust superresolution by using the second generation wavelet is identified.

The contributions of this research also includes an analysis of the displacement errors on the convergence rate of the iterative approach for solving the transform based preconditioned system of equations. Subsequently, it is established that the use of the MAP, L_2 norm or H_1 norm regularization functional leads to a proof of linear convergence of the conjugate gradient method in terms of the displacement errors caused by the imperfect subpixel locations. Results of simulation support the analytical results. We remark that when the L_2 norm or H_1 norm regularization functional is used, the corresponding regularization

matrices under the Neumann boundary condition can be diagonalized by the discrete cosine transform matrix. Thus if we use the Neumann boundary condition for both the blurring matrix $\mathbf{H_L}$ and the regularization matrix then the coefficient matrix $\mathbf{H_L^t H_L} + \alpha \mathbf{P^t P}$ can be diagonalized by the discrete cosine transform matrix and hence its inversion can be done with three 2-dimensional fast cosine transforms (one for finding the eigenvalues of the coefficient matrix, two for transforming the right hand side and the solution vector; see [14] for instance). Thus the total cost of solving the system is of $O(M_1 M_2 \log M_1 M_2)$ operations. Here g is an $M_1 \times M_2$ image and is called the *observed high-resolution image.* . We interlace the low resolution images to form an $M_1 \times M_2$ image by assigning

$$g[L(n_1 - 1) + l_1, L(n_2 - 1) + l_2] = g_{l_1 l_2}[n_1, n_2]. \tag{1}$$

We have showed that the spectra of the preconditioned matrices are clustered around 1 for sufficiently small $\bar{\epsilon}$ [10].

Another important contribution of this research is the regularized constrained total least squares formulation and solution of the high resolution image reconstruction problem with multisensors [11]. The regularization parameter used is obtained by the L-curve method [15]. The numerical algorithm developed is iterative and involves a two-step minimization strategy at each iteration. Each step, in turn, involves the least-squares solution of a convex optimization problem, though the overall problem is nonconvex. A characteristic of the numerical strategy developed is the decrease of the cost functional with increase in the number of iterations.

5 Listing of Publications

5.1 Papers Published in Peer-Reviewed Journals

The following papers were published in peer-reviewed journals where support from the grant was acknowledged.

1. M. K. Ng and N. K. Bose, "Analysis of Displacement Errors in High-Resolution Image Reconstruction," invited paper in Special Issue on Multidimensional Signals and Systems, IEEE Trans. Circuits and Systems-I, vol. 49, no. 6, June 2002, pp. 806-813.

2. M. K. Ng, J. Koo and N. K. Bose, "Constrained Total Least Squares Computations for High-Resolution Image Reconstruction With Multisensors," Journal of Imaging Science and Technology, John Wiley and Sons, Inc.,12, no.1, 2002, pp. 35-42.

3. S. Lertrattanapanich and N. K. Bose, "High Resolution Image Formation from Low Resolution Frames Using Delaunay Triangulation," IEEE Transactions on Image Processing, vol. 17, December 2002.

4. M. K. Ng and N. K. Bose, "Fast Color Image Restoration With Multisensors," Journal of Imaging Science and Technology, John Wiley and Sons, Inc., accepted for publication.

5. M. K. Ng and N. K. Bose, "Mathematical Analysis of Superresolution Methodology," IEEE Signal Processing Magazine, 2003, invited paper.

5.2 Papers Published in Peer-Reviewed Conference Proceedings

1. N. K. Bose, S. Lertrattanapanich and J. Koo, "Advances in Superresolution Using L-curve," Proceedings of the International Symposium on Circuits and Systems (Sydney, Australia), Vol. II, May 6-9, 2001, pp. 433-436.

2. N. K. Bose and S. Lertrattanapanich, “Advances in Wavelet Superresolution,” SAMPTA 2001 Proceedings of the International Conference on Sampling Theory and Its Applications (Orlando, Florida), May 13-17, 2001, pp. 5-12.

3. S. Lertrattanapanich and N. K. Bose, “High Resolution Image from Multiframes by Delaunay Triangulation: A Synopsis,” ICIP-02: Proceedings of IEEE International Conference on Image Processing (Rochester, New York), Vol. 2, September 2002, pp. 22-25.

5.3 Papers Presented in Meetings but not Published in Conference Proceedings

1. N. K. Bose, “ Towards Blind Robust Superresolution, ” Opening Invited Lecture at the Workshop on Mathematics in Image Processing, The University of Hong Kong, December 14, 2000.

2. N. K. Bose, “Groebner Bases, Polynomial Matrix Factorization, Multidimensional Filter Banks and Wavelets,” Opening Session Invited Lecture at SAMPTA 2001 Proceedings of the International Conference on Sampling Theory and Its Applications, Orlando, Florida, May 14, 2001.

6 Advanced Degrees Received by Scientific Personnel Involved In The Project

The following students were partly supported by funds from the project.

1. Surapong Lertrattanapanich has scheduled his Final Ph. D. Defense on December 10, 2002. His dissertation is entitled “Superresolution from Degraded Image Sequence Using Spatial Tessellations and Wavelets.”

2. Jaehoon Koo is expected to schedule his Final Ph. D. Defense by February 28, 2003. His dissertation is entitled "High Resolution Image Recostruction from Multiple Degraded Images Acquired with Multisensors."

3. Hung-Sik Kim received his Master of Science Degree in December 2001. His thesis is entitled "Reconstruction and Classification of Image from Noisy Phase and its Coding." He has now been admitted to the Ph. D. Program.

4. Chih-Chung Yang is working towards his Ph. D. He passed his Comprehensive Examination on Novemmber 2001 and wrote a dissertation proposal entitled "Automated Landmine Detection Using Computational Intelligence."

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[1] N. K. Bose, “Improved Landmine Detectioon by Complex-Valued
Artificial Neural Network: Annual Progress Report,””
submitted to U. S. Army Research Office, September 06, 2001.

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SIAM J. Sci. Comput., 21 (1999), pp. 851–866.

[15] N. K. Bose, S. Lertrattanapanich, and J. Koo, " Advances in superresolution using the L-curve, " *Proceedings of International Symposium on Circuits and Systems,* Sydney, Australia, Vol. II, pp. 433–436, May 2001.

[16] N. K. Bose and K. Boo, "High resolution image reconstruction with multisensors," *International Journal of Imaging Systems and Technology,* 9 (1998), pp. 294–304.

7 Appendix of Figures

Figure 1: To evaluate the importance of phase information in the presence of noise in image reconstruction. Reconstructed image from phase only information has many important features in common with the original image. Also, reconstruction from noisy phase (and original magnitude) is more robust to error than reconstruction from noisy magnitude (and

original phase). Therefore, phase only information can be used for various applications like signal reconstruction, landmine classifier, and so on.

Figure 2: To assess the importance of noise-corrupted, degraded and partial phase information in object classification by artificial neural network (ANN) in applications like landmine identification and classification. Phase information is more error-tolerant than magnitude information in terms of signal reconstruction. The number of input neurons can be reduced to adequate size to simplify ANN and decrease ANN training time. Therefore, partial phase only information can be used as input data in object classification by ANN

Figures 3: Shows the overall strategy for blind robust superresolution using either first generation wavelets or spatial tesselation.

Figures 4-9: These figures show selected frames from a real video sequence, panoramic videomosaic costructed after video camera motion parameter estimation, and the results following implementation of superresolution algorithm (Delaunay triangulation based) on two selected ROIs in the mosaic.

Figures 10-12: Multiple images mean image sequences of monochrome or multispectral images, here. Image sequences are produced from snapshots of an object or scene, or from the multisensor array system while multispectral images are acquired by multiple sensors with wavelength optical filters. For background and notation, see the original paper by Bose and Boo [16].

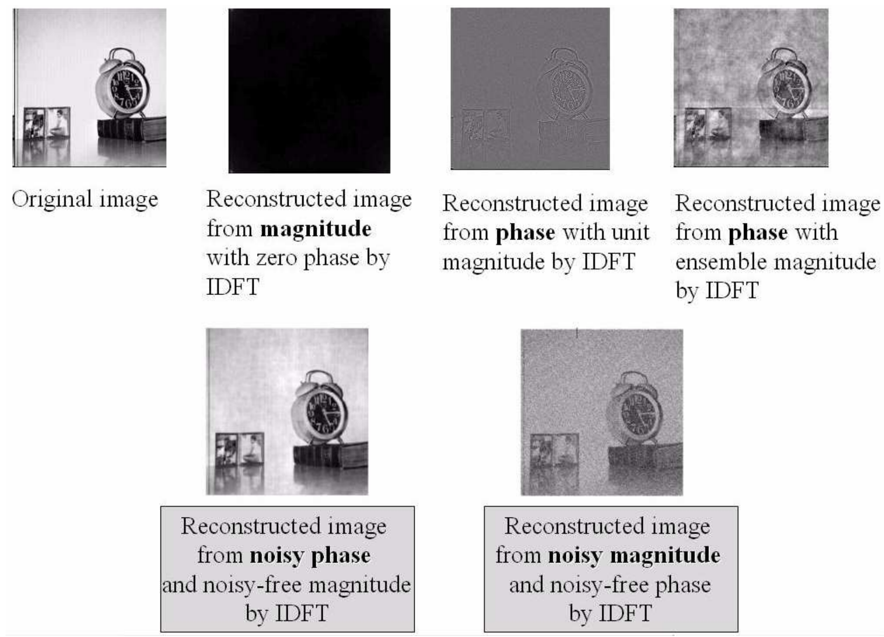

Figure 1: Original image and reconstructed images

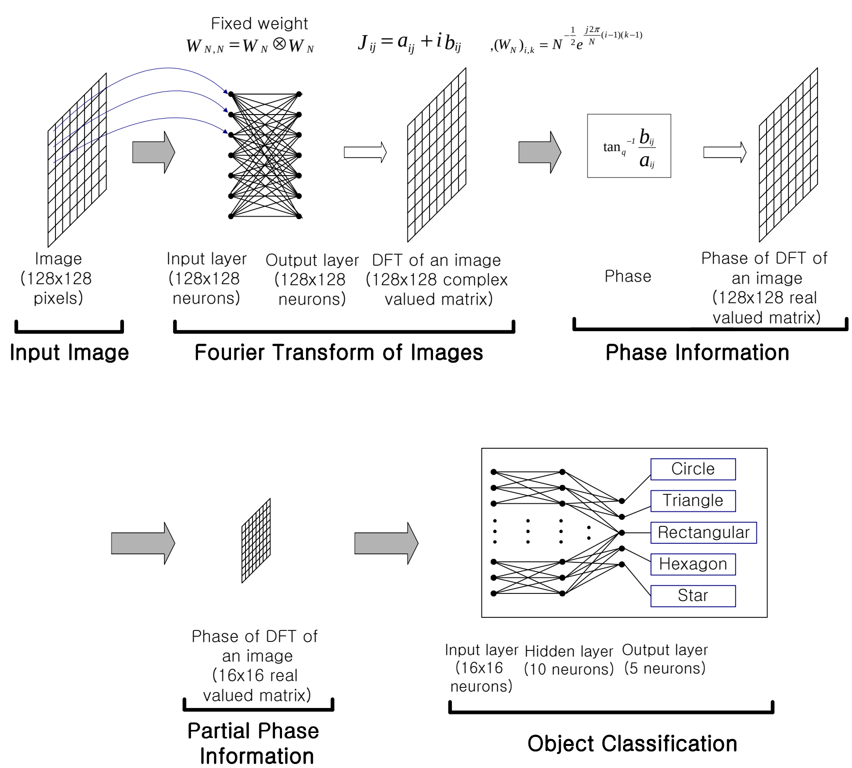

Figure 2: Overall neural network for object classification

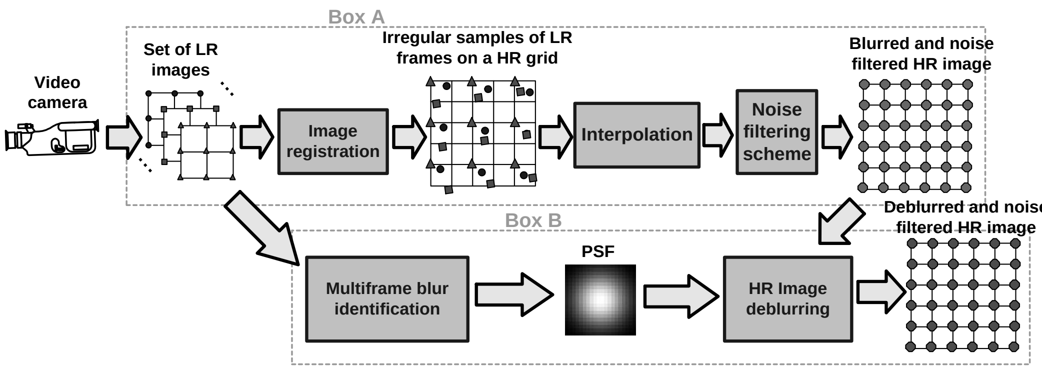

Figure 3: The HR image reconstruction can be divided into two parts: interpolation and restoration. The image registration is the inverse geometric transformation. It transforms LR samples into a HR grid. The multiframe blur identification part estimates the point spread function (PSF) of blur from the set of LR images, either directly or indirectly, and then used in the restoration part.

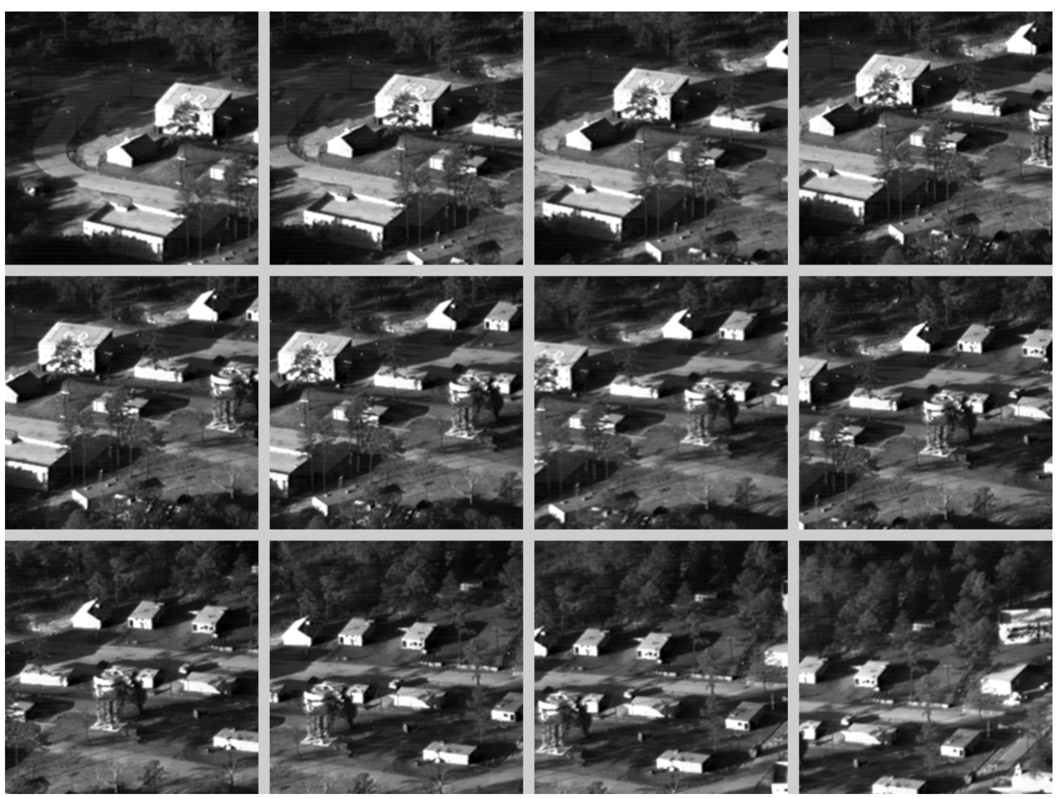

Figure 4: Some LR frames in the real video sequence

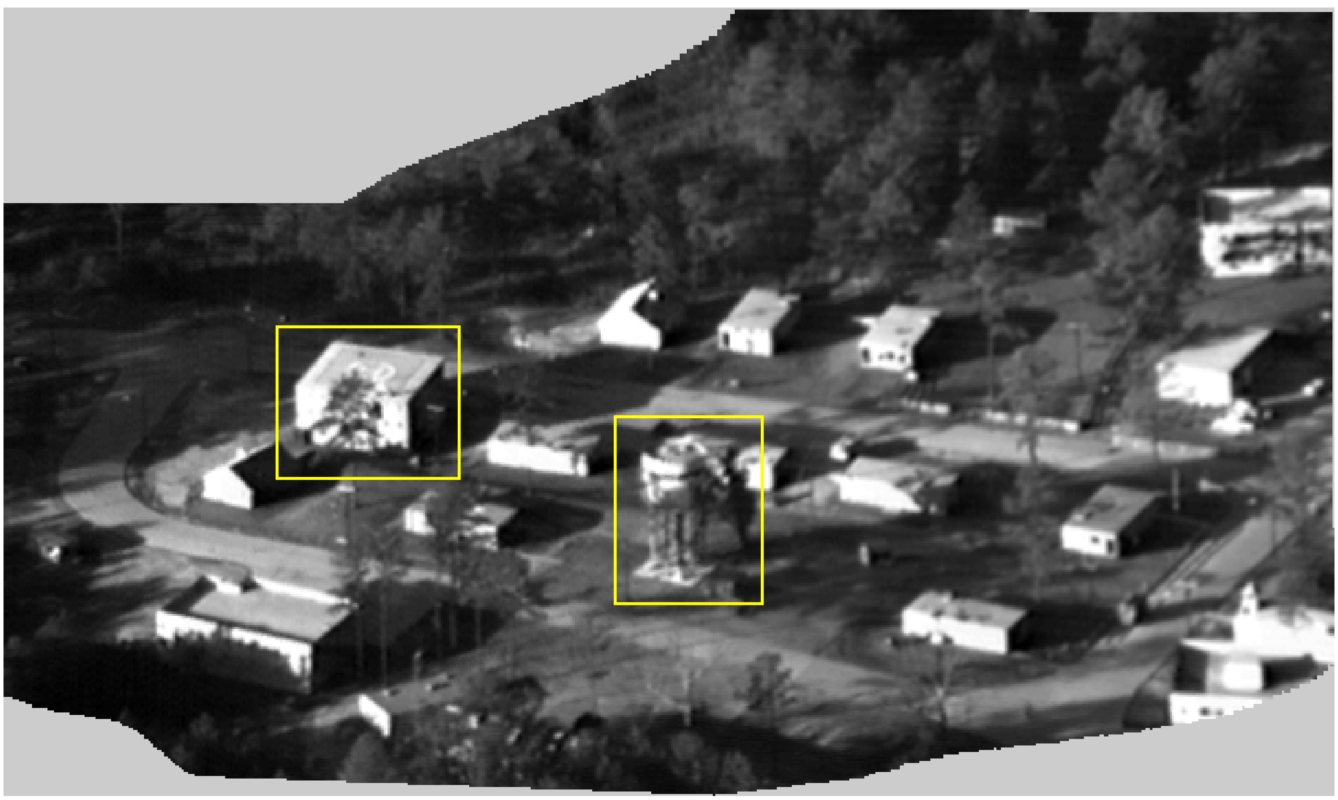

Figure 5: Video mosaic with the boundary of ROIs

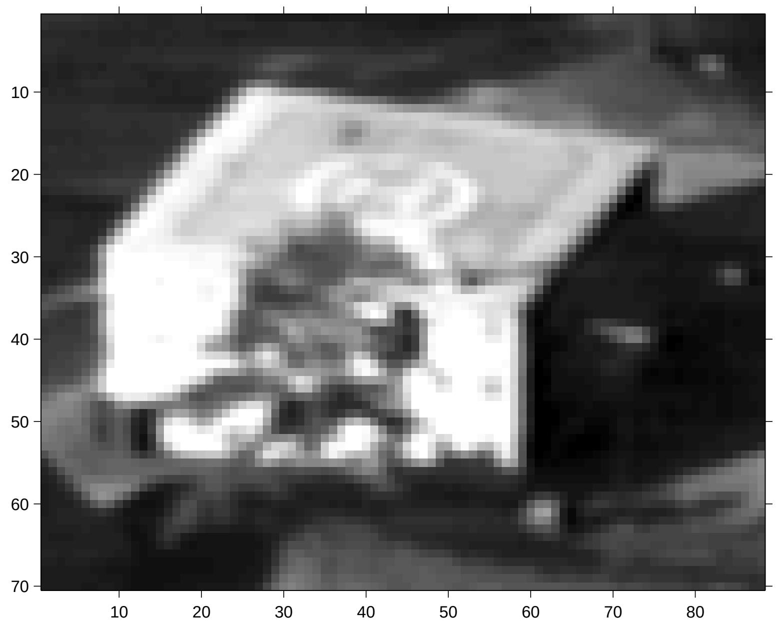

Figure 6: Sample of LR frames in ROI-1

Figure 7: HR image of ROI-1

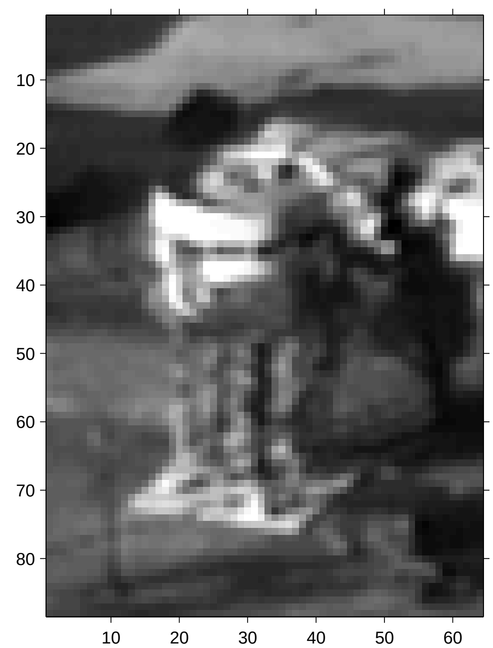

Figure 8: Sample of LR frames in ROI-2

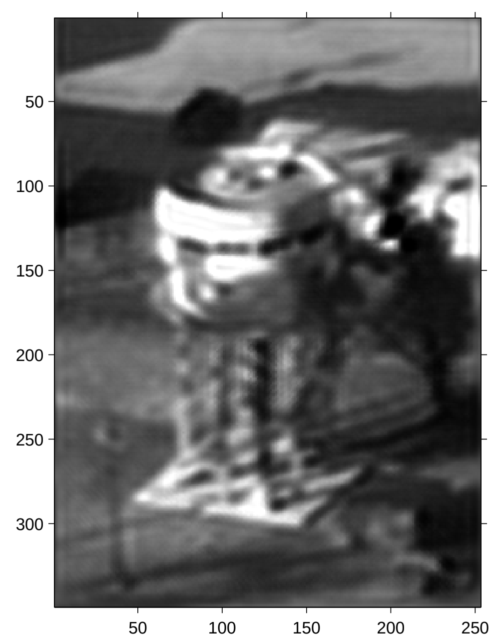

Figure 9: HR image of ROI-2

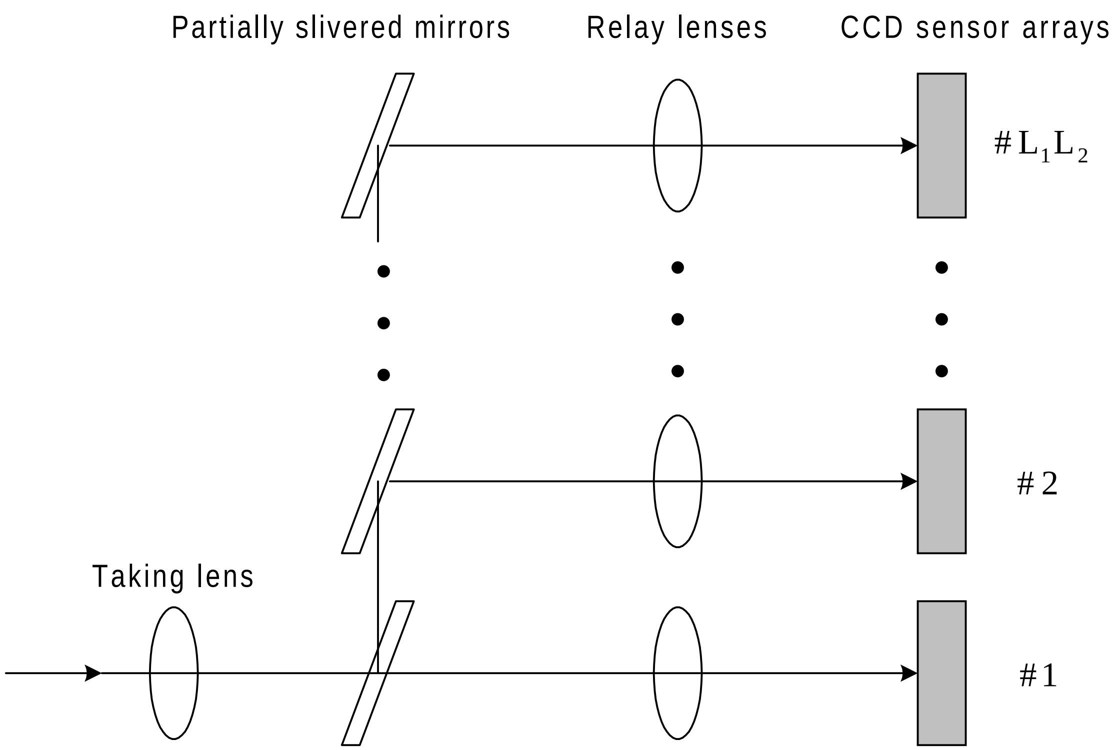

Figure 10: Image formation systems by using multiple CCD sensor arrays

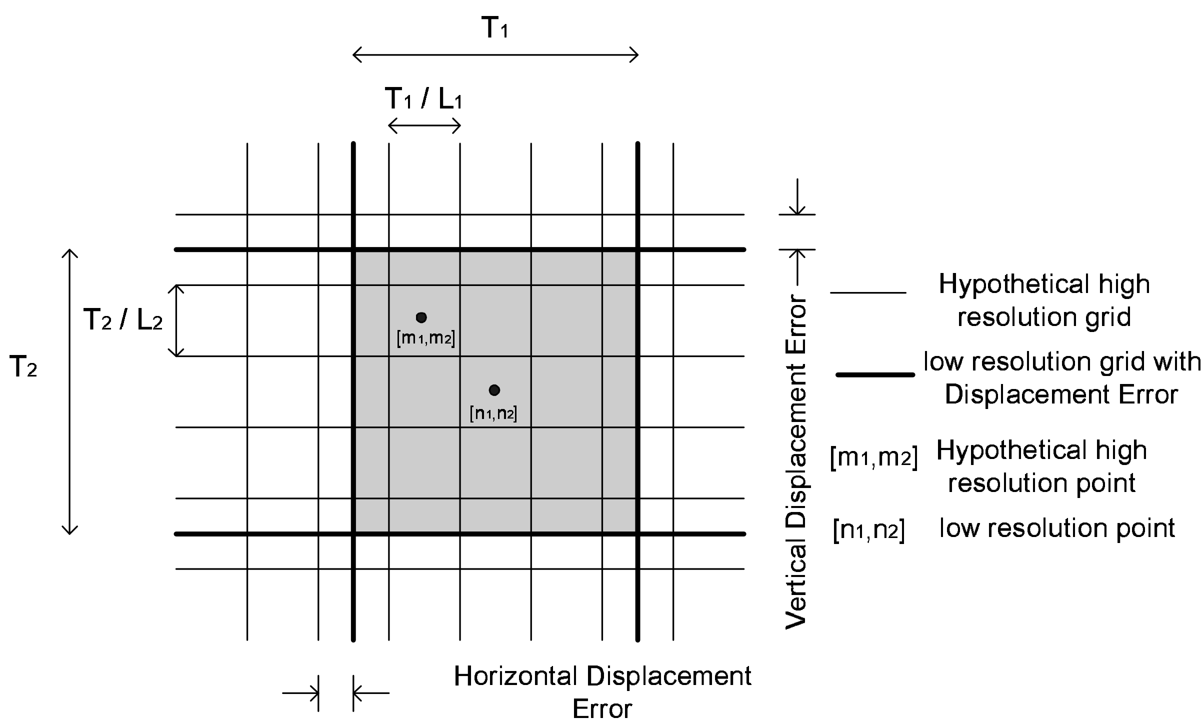

Figure 11: The relationship between high and low resolution image sensors

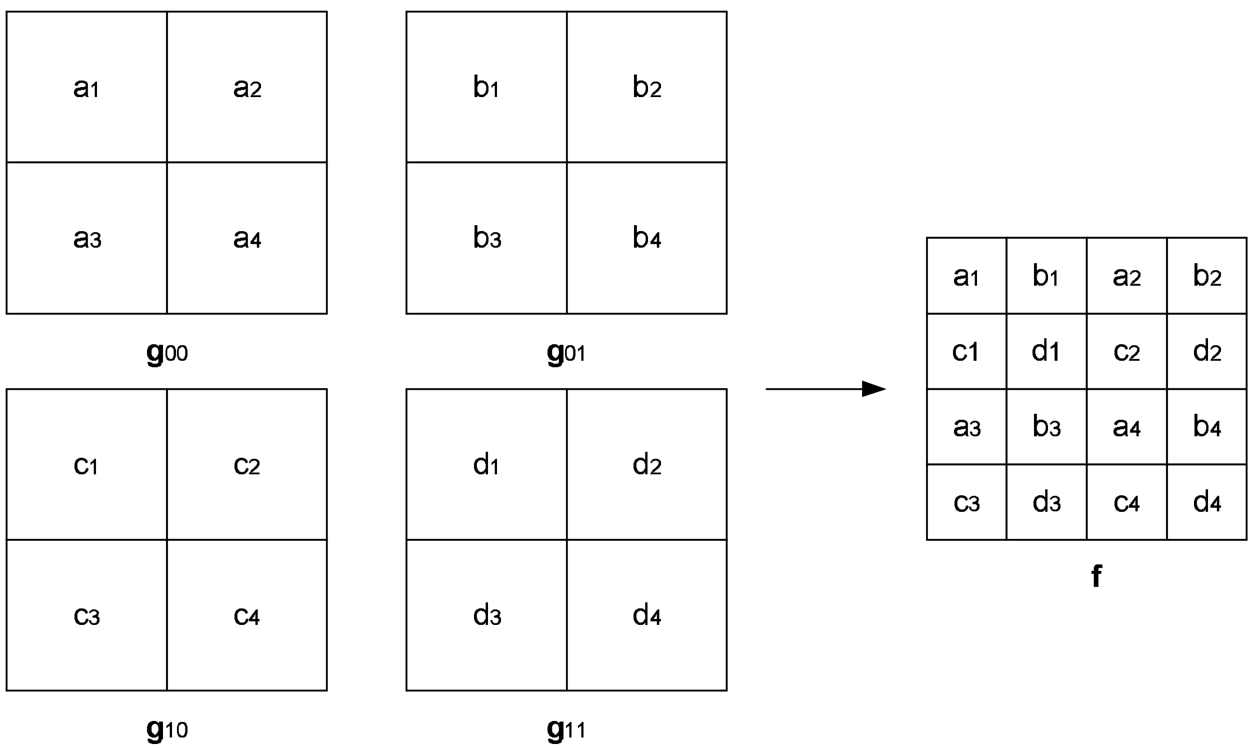

Figure 12: Example of **HR** image reconstruction from a set of degraded **LR** images when $L_1 = L_2 = 2$